On the Role of Political Affiliation in Human Perception

The Case of Delhi OddEven Experiment

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ABSTRACT

In an effort to curb air pollution, the city of Delhi (India), known to be one of the most populated, polluted, and congested cities in the world has implemented the first phase of OddEven experiment in the period January 1st-15th, 2016. During the experiment, most of four-wheeled vehicles were constrained to move on alternate days based on whether their plate numbers ended with odd or even digits. While the local government of Delhi represented by A. Kejriwal (leader of AAP party) advocated for the benefits of the experiment, the prime minister of India, N. Modi (former leader of BJP) defended the inefficiency of the initiative. This particular configuration has led to a strong polarization of public opinion towards OddEven experiment, which provided the scientific community with a unique opportunity to study the impact of political leaning on humans perception of large-scale and real-world urban experiment. We collect data about pollution and traffic congestion to measure the real effectiveness of the experiment. We use Twitter to capture the public discourse about OddEven and study citizens opinion within different dimensions: time, location, and topics. Our results reveal a strong influence of political affiliation on how people perceived the outcomes of the experiment. For instance, AAP supporters were significantly more enthusiastic about the success of OddEven compared to BJP supporters. However, taking into account location of people revealed that personal experience is able to overcome political bias.

KEYWORDS

Urban Analytics; Urban Policy Making ; Computational Social Science; Political Science.

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1 INTRODUCTION

Context. Delhi, the home of more than twenty millions inhabitants, is one of the world's most densely populated cities [20]. The city has grown rapidly, and expanded geographically in the last years. This increase has enlarged the challenges for the urban transport systems, resulting critical air quality levels, endless traffic congestion, and alarming accident rates [18]. Thus, political leaders and decision makers are striving to take the lead in combating these challenges to improve the accessibility and enhance the livability in the city. As a practical step towards crystallizing this goal, the city of Delhi has launched on the demand of the Supreme Court an urban initiative to reduce air pollution. With more than nine million registered vehicles in Delhi, Aam Aadmi Party (AAP) led an initiative coined as `OddEven` experiment to tackle the issue by allowing *non-transport four-wheeled vehicles* to move on alternate days based on whether their registration number ends with odd or even digits. The first phase of the 15-day pilot took place in Delhi from January 1st to January 15th, 2016. It is important to notice that over 20 categories were exempted from this rules. Examples for such omissions are women only vehicles, vehicles belonging to some government agencies, and vehicles occupied by handicapped persons. Full description of the experiment as per the official notification can be found in this document [4]

Air Pollution and road traffic. Air pollution is a major problem in many cities around the world. In an urban context, it is often the case that air pollution is tightly associated with road traffic and congestion [21] Thus, it is not surprising that many cities adopt traffic related plans and actions such as car bans, alternate driving, and "congestion charges" to control for air pollution. December 7, 2016 Paris authorities restricted traffic in the city for a second day as it battled a peak in air pollution that posed a significant risk to resident health. Restrictions concerned cars with even numbers (odd numbered cars were banned the day before), and the whole public transportation system in the city was made free on these two days [3]. Singapore adopted a new strategy to tax drivers entering the city center. In London, a congestion fee was adopted in 2003 to cut down traffic. Other cities like San Francisco, Turin, Genoa, and Oslo have adopted similar approaches [13], all to curb air pollution.

The urban experiment. Understanding the impact of urban experiments would effectively lead to design better public strategies and policies. However, assessing the success of these experiments is often hard and tedious as many parameters need be controlled. For instance, the success of an experiment can be measured by looking at the strict impact it had on the expected outcome. Doing so, we might be missing important secondary effects of the experiment on people's daily lives that we did not anticipate. Therefore, it is of a paramount importance to include people opinion in such circumstances. Delhi `OddEven` experiment provides a unique opportunity to study the political bias and preconceptions affecting human perceptions toward the outcomes of a large-scale and real-life experiment. In fact, while Delhi state government led by Arvin Kejriwal, *leader of the AAP party*, claimed that `OddEven` experiment would result in an improved air quality and eventually a decreased traffic congestion, the principal opposition party in Delhi *BJP, previously led by India PM*, argued that the experiment will have no impact but disturbing people's daily commute in the city. In order to track the public discourse toward this experiment, we propose to distinguish three major phases illustrated in Figure 1.

- ***Anticipation:*** This is the period that preceded the experiment. It ranges from December 15, 2015 to January 1, 2016. This phase is important as it allows us to understand the expectation of people toward `OddEven`. A. Kejriwal announced the starting date of `OddEven` experiment on the beginning of December.
- ***Experience:*** From January 1 to January 15. This is the "actual experience" period during which the experiment took place. We expect people to share and express their opinion as they live the experiment.
- ***recollection:*** This is the period after the experiment. It starts on January 15 and ends on January 30. This phase is important in that it allows to track what people feel about the situation going back to normal in their city.

Note that each of the three phases lasts for two weeks (15 days.)

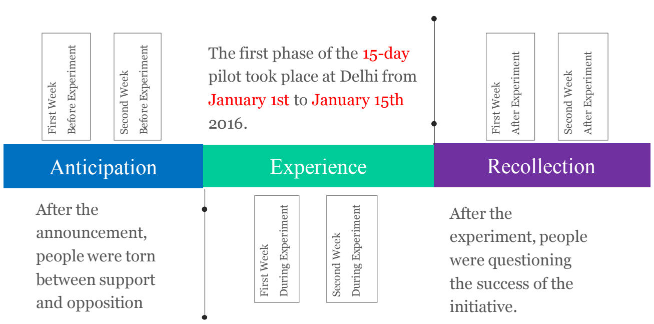

Figure 1: The three temporal phases of `OddEven` experiment. Before (anticipation), within (experiment), and after (recollection).

Literature review. Although `OddEven` took place in Delhi, the experiment attracted national and international attention. In our study, we are interested in understanding people opinion with a focus on political and spatio-temporal factors that shaped the public discourse. This paper contributes to a growing body of literature on exploiting social media platforms to better understand human behavior that lies at the intersection of social, political, and urban sciences. Researchers in this areas have focused on studying human social interactions on twitter to better understand their opinions in general and their political views in particular [5, 7, 8, 10, 12, 15, 16]. Barber [5] has developed a *Bayesian spatial following* model that takes into account users Twitter network to estimate the ideology of political leaders and that of average citizens in several countries, including United States,United Kingdom, Spain, Italy, and the Netherlands. The main finding of the author was an efficient inference of users political leaning based solely on Twitter structural network. Another work by Barber [6] builds on 12 political and non-political events to understand the role of social media in the formation of polarized groups as well as user opinion. The key finding is that during certain political-driven events, individuals with similar political orientation tend to engage in discussions and share similar opinions, creating what is known as *echo chamber*. This corroborates Pennacchiotti and Popescu observations according to which social platforms have the potential to amplify the importance of peer effects in political behavior [17]. This is particularly true as users naturally interact with like-minded people who most probably share the same political views. Other attempts to infer the political leaning of users include Golbeck and Hansen work of using Twitter following relationships to infer political preferences [14], and Colleoni et al. who use a combination of machine learning and social network analysis to categorize users as Democrats or Republicans based on what they share on social networks [9].

Research Questions. The current literature does not offer a comprehensive overview on using social interactions to assess the impact of political bias in how large scale urban initiatives are perceived by people. Thus, we formulate the following research questions: The objective of this paper is to understand the political factors that contribute to citizens' perception towards the urban initiative. The main research questions are summarized as follows:

- **RQ1** Does political affiliation influence people perception and opinion about real-life experiment?
- **RQ2** Does personal experience have any impact on reducing political bias and preconceptions?
- **RQ3** Is there enough publicly available data that one could use to address such inquiries?

Approach and contributions. To run this study, we use Twitter to sense the public discourse toward `OddEven` experiment. A list of relevant keywords has been manually created and was continuously curated to catch relevant tweets. The obtained collection consists of more than 300K tweets posted by 64K different users. It spans from December 17th, 2015 to February 5th, 2016 covering most of the three phases of the experiment: anticipation, Experience, and recollection. We collect the contextual urban data about the experiment to quantify the actual impact of `OddEven` on air quality and traffic congestion. We use data from the Central Pollution Control Board program (CPCB)[1] for its reputation and completeness to track hourly levels of Particulate Matter (e.g., PM2.5). Similarly, we use Google Traffic API to estimate hourly levels of the traffic congestion in Delhi by continuously querying routes for 22 origin-destination pair samples carefully selected to reflect the actual status of congestion in Delhi.

[1] http://www.cpcb.gov.in/

We use Twitter data (Content) to infer the political leaning of users as well as their locations. Users are then clustered based on these two dimensions. For each cluster, we use sentiment analysis to assess the overall opinion of groups toward different topics (air quality, traffic congestion, and public transportation) during the three phases of the experiments. Our analysis reveals the following key findings:

- Overall, political formation play a significant role in the way people perceive the outcome of natural experiments. Interestingly enough, we found that event people who live outside Delhi and India, had strong opinions about the success or not of the experiment.
- Personal experience is able to overcome political bias. This was the case when we limited the analysis to only users living inside Delhi, i.e., those who have had a personal experience of `OddEven`.
- Overall, people where satisfied with the public transportation infrastructure that could handle the significant and sudden surge in demand.

Roadmap. In what follows, we start by describing the different datasets that we used to study people's opinion. Then, we introduce the methods that are used to sense people's opinions as well as quantifying the political affiliation of twitter users. Next, we study and discuss the findings based on people's opinion and their engagement based on different dimensions.

2 DATA

To make this study possible, we needed to collect and integrate data from different sources. Social sensing of Twitter is used to track public opinion about `OddEven` whereas physical sensing data about air quality and traffic congestion is used to estimate the actual outcomes of the experiment. We describe in the following the processes by which data is collected and curated from different sources.

2.1 Twitter

Collecting relevant tweets. The data collection process was carried out using the Twitter Streaming API, which is publicly available. First, we build a list of seed hash-tags that are used during experiment. Then, we expand this list to identify more tweets that could be potentially used people to react to new developments of the experiment. The final list contains the following keywords/hashtags: `OddEven`, *Odd Even*, *ToxicDelhi*, *ICantBreathe*, *Delhi*, *EvenOddFormula*, *DelhiChokes*, *LetDelhiBreathe*, *NationalGreenTribunal*, *DelhiOddEvenLogic*, *DelhiPollution*, *pollutionfreeDelhi*, *IPledgeForOddEven*, *IamWithOddEven*, *EvenYourOdds*, *OddEvenMovement*, *OddEvenPlan*, *OddEvenFormula*, and *EvenOddPlan*. Finally, we employ various techniques to clean the data. The cleaning steps include the removal of irrelevant tweets containing hashtags related to `OddEven`. Indeed, it is common in Twitter for people and bots to include trending hashtags in their tweets even when the hashtags are completely irrelevant to the content of their tweets. The heuristic we used was to generate timely sets of top 100 frequent hashtags, and then manually black-list accounts and hashtags that are not relevant to our study.

The collection process spans across six weeks, starting from December 17th, 2015 to February 5th, 2016, covering two weeks before, during and after the experiment. The result of our dataset after filtering the non relevant data is 320,450 tweets, posted by 63,988 unique users. Figure 2 shows the volume of tweets as well as the number of active users over time.

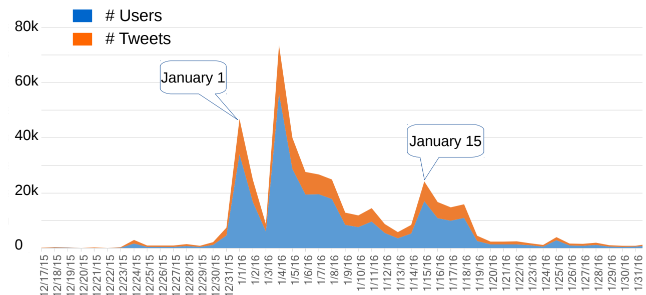

Figure 2: Distribution of tweets and users discussing #OddEven experiment. Most of Twitter traffic took place during the experience. We observe that the recollection period was quite active compared to the anticipation period.

Collecting network data. We identified Twitter accounts that authored at least one tweet related to `OddEven` experiment and we requested their network information (followers and followees) as well as up to 3,200 of the latest tweets they authored or re-tweeted. Note that as per Twitter policy, it is not possible to retrieve more than 3,200 per user.

2.2 Air Quality

In order to measure the success of the experiment with respect to air quality improvement, we collected environmental data to sense pollution levels in the city. Our exploration allowed us to identify and compare different data sources that offer Air Quality datasets. Examples of such open platforms include:: U.S. Embassy air Quality Monitoring Station[2], BREATHE INDIA SPEND[3], DPCC Program[4], and CPCB Program[5]. In our study, we use Central Pollution Control Board program (CPCB), an initiative of the ministry of environment in India, that provides much richer and complete datasets. From this data, we mainly rely on the levels of the particulate matter PM2.5 to measure the quality of air in the city. We mainly focus on two stations "Shadipur" located in the city center and "Dwarka" located in a suburb neighborhood as illustrated in Figure 4. The figure also shows the important number of industries inside and surrounding the city of Delhi that may have a significant impact on the air quality regardless of `OddEven` experiment. We have also collected weather data in order to account for wind speed and direction in the analysis.

2.3 Road Traffic Congestion

With the help of Delhi-born scientists part of this project, we manually and carefully identified a short list of road segments (origin-destination pairs) reputed to be of the most congested in Delhi. We also identified the main surrounding agglomerations of Delhi and

[2] http://newdelhi.usembassy.gov/airqualitydata.html
[3] http://breathe.indiaspend.org/
[4] http://www.dpccairdata.com/
[5] http://www.cpcb.gov.in/

created routes from-to Delhi to those cities. The full list of selected routes is given hereafter (See Figure 3 for a visual inspection of the selected routes): Asaf Ali → CP, Gandhi Airport → CP, SadarBazarRailway → CP, MandiHouse → CP, DelhiHeartLungInstitute → CP, CP → DelhiHeartLungInstitute, CP → SadarBazarRailway, CP → GandhiAirport, CP → MandiHouse, CP → Asaf Ali, Ghaziabad → Delhi, Gurgaon → Delhi, Bahadurgarh → Delhi, Sonipat → Delhi, Noida → Delhi, Faridabad → Delhi, Delhi → Bahadurgarh, Delhi → Noida, Delhi→ Faridabad, Delhi → Sonipat, Delhi → Ghaziabad, Delhi → Gurgaon.

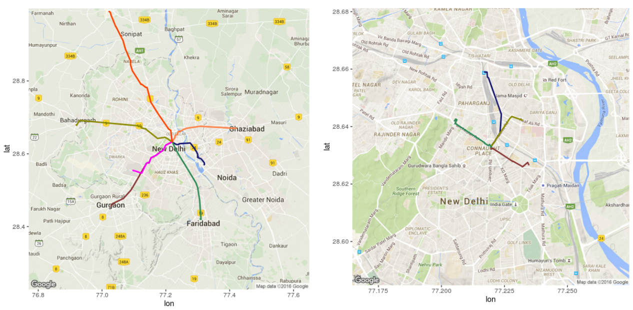

Figure 3: Illustration of the routes sampled to estimate the congestion level in Delhi. The right panel showcases major highways linking the city of Delhi to its neighboring suburbs. The left panel is a zoom-in into Delhi's central business district (Connaught Place) and covers some small road segments in intramural Delhi known for their chaotic congestion.

We use the direction request of Google Maps API [6] to request the timely details about the traffic status for the list of road segments every 15 minutes. Our objective is to track Travel Time (TT) for each origin-destination route at different times of the day, different days of the week; before, within, and after the experiment. Thus, for each route r we build a time series $TT_r(t)$ that reports the travel time in seconds for route r at time t. We define a timeless congestion factor (C_f) to estimate the level of congestion for each route r_i at time t_j as follows:

$$C_f(r_i, t_j) = \frac{travel\_time(r_i, t_j)}{free\_flow(r_i)}$$

where $free\_flow(r_i)$ is nothing but the minimum travel time observed for the route r_i, i.e., $free\_flow(r_i) = min_{j \in T}(TT_{r_i}(t_j))$, T is the discretized time interval of the experiment (one time-stamp value every 15 minutes). $travel\_time(r_i, t_j)$ is the actual travel time of r_i at time t_i. The intuition here is that the minimum travel time is naturally observed in a free-flow scenario (e.g., 03:00 AM early in the morning) and hence the congestion level at any time of the day can be computed as the fraction of the actual observed travel time divided by the free-flow travel time. The daily congestion factor of route (r_i) in day d_k, $C_f(r_i, d_k) = median_{j \in d_k}\{C_f(r_i, t_j)\}$. Similarly, the overall congestion factor in the city in day d_k is obtained by averaging the congestion factors observed in all routes, $C_f(d_k) = \frac{1}{n} \times \sum_{i \in len(routes)} C_f(r_i, d_k)$. Figure 5 reports the distribution of daily congestion factors observed at different routes (light gray) and the average congestion factor of the whole Delhi (dark blue.) A best-fit line is also reported.

[6]Google Maps API: https://developers.google.com/maps/documentation/directions/intro

Unfortunately, due to some technical limitations, we were able to collect this data starting from the 3rd of January which coincides with the third day of the experiment.

3 THE GROUND REALITY

In order to understand the perception of Twitter users toward the experiment, it is important to assess the ground reality and measure the extend to which *OddEven* succeeded in fulfilling its main goal of reducing air pollution, as well as its impact on traffic congestion.

3.1 Impact on Air Pollution

We analyze the time series of PM2.5 readings obtained from two stations: Dwarka and Shapidur. The analysis is split into three time periods corresponding to the three phases of the experiment: anticipation, experience, and recollection.

The term fine particles, or particulate matter 2.5 (PM2.5) refers to tiny particles or droplets in the air that are two and one half microns or less in width. Fine particulate matter is an air pollutant can be harmful for people's health when its levels in the air are high. This is why public authorities are taking drastic measures to combat it. Examples include the city of Paris that banned half of cars and made its public transportation system free to ride on two days in December 2016 [3]. In the same month, the city of Beijing ordered the shutdown of over 1,200 factories because of alarming levels of air pollution [1].

Our objective here is to statistically compare the levels of PM2.5 between the three periods (before, during, and after `OddEven`) using T-tests pairwise in order to validate the hypothesis according to which air pollution decreased. Our main conclusion was that PM2.5 levels have increasing trends for both stations when we compared the readings for the periods anticipation (before) and experience (during.) The trend was strongly statistically significant for this particular comparison with 95% confidence interval and a two-tailed P-value less than 0.0001. The augmentation of air pollution was also significant for Shadipur station when we compared the phases of experience (during) and recollection (after).

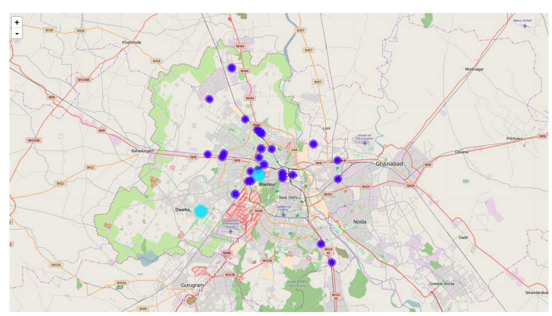

Figure 4: Air quality stations Dwarka and Shadipur (light blue) in Delhi industrial areas (purple spots).

The increase of air pollution could be explained by the industries in the region and stubble burnings that are prevalent in the surroundings of Delhi at this period of the year. Thus we further deepen our analysis by taking into account the wind speed and direction in different periods of the experiment. Unfortunately, even these meteorological parameter did not explain the significant increase in the air pollution. Given all these observations, we can safely argue that `OddEven` did not have any significant impact on air pollution in Delhi.

3.2 Impact on Traffic Congestion

We analyzed Google Traffic data for the predefined pairs of origin-destination routes in Delhi and we compare the minimum, maximum, and average durations (travel time) of the trips during and after the experiment. We run T-test to evaluate the significance of the hypothesis that the travel time has been reduced during experiment compared to the travel time after the experiment. Our observation is that this hypothesis is actually confirmed and the traffic condition in Delhi and its suburbs has significantly improved during the experiment in most of the origin-destination trajectories as indicated in the last columns of Table 1.

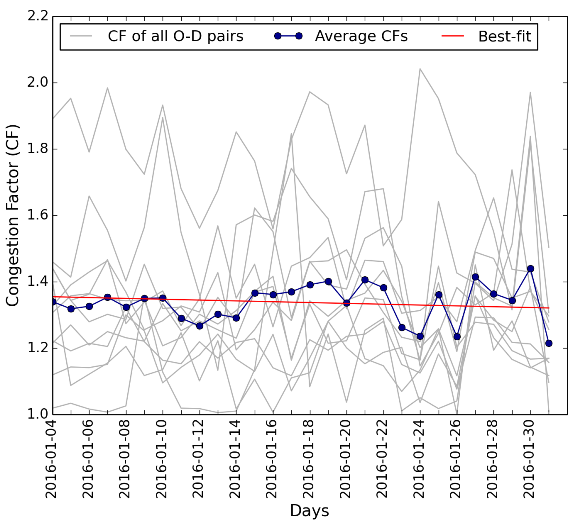

Figure 5: Congestion levels from January 3 to January 31. The best fit line is plotted in red and shows a significant decreasing trend in congestion levels ($slope = -0.00125, p - value = 5.5e^{-6}$).

Figure 5 illustrates the temporal distribution of the daily congestion factor observed in the city of Delhi. Recall that this is a proxy that we obtained by averaging congestion levels of 20 important origin-destination pairs. The best fit line (in red) shows a negative slope ($\alpha = -0.00125$) that is statistically significant ($p - value = 5.5e^{-6}$.) The fact that the traffic congestion did not go up in the recollection phase can be due to the way Google compute the travel time. According their official documentation[7], this is done by combining historical traffic with live traffic, which means that major changes to the traffic need some time before they are accurately reflected in the prediction model.

[7] https://developers.google.com/maps/documentation/directions/intro#traffic-model

Table 1: T-Test of travel time (TT) differences (in mn) during minus after the experiment. M.D. is the maximum TT difference in minutes. HS: highly significant, S: significant

origin	destination	t-score	p-value	M.D.	Conc.
AsafAli	ConnaughtPlace	-4.1134	0.0006	-670	HS
Bahadurgarh	Delhi	-38.7695	7.52E-14	-2426	HS
ConnaughtPlace	HeartLungInstitute	3.2097	0.0013	-6	HS
ConnaughtPlace	GandhiAirport	-2.3995	0.0165	-215	S
ConnaughtPlace	MandiHouse	-3.2507	0.0012	-235	HS
Delhi	Bahadurgarh	-6.3031	4.37E-10	-785	HS
Delhi	Faridabad	4.6183	9.36E-06	-289	HS
Delhi	Ghaziabad	3.7554	0.0195	-1496	S
Delhi	Gurgaon	-2.0123	0.0443	-1027	S
Delhi	Noida	2.4844	0.0159	-124	S
Delhi	Sonipat	2.9826	0.0202	-1462	S
HeartLungInst.	ConnaughtPlace	-3.1068	0.0019	-433	HS
Faridabad	Delhi	-10.6980	1.23E-17	-1661	HS
GandhiAirport	ConnaughtPlace	44.8939	3.59E-37	-774	HS
Gurgaon	Delhi	-2.3387	0.0406	-1148	S
MandiHouse	ConnaughtPlace	-3.0009	0.0063	-350	HS
Noida	Delhi	-11.4465	1.46E-25	-1140	HS
SadarBazarRailway	ConnaughtPlace	3.0421	0.0024	-127	HS
Sonipat	Delhi	16.6277	0.0296	-1636	S

4 METHODS

Recall that our main objective is to verify whether or not political affiliation influences human perception in real life urban experiments such as `OddEven`.

The first task is to identify the political leaning of users. We use Twitter data if the form of content of tweets, hashtags, mentions, user biographies, and social links (friends and followers) in training different multi-class classifiers to infer one of the four political labels: (1) AAP supporters, (2) BJP supporters, (3) Bi-political, and (4) Apolitical. We manually labeled a training set by looking at users who mentioned their political affinities in their Twitter biographies. Surprisingly enough, we found that the political leaning of users can be accurately inferred by looking at people and accounts they follow. More details and discussions will be reported in the next section.

The second task is to mine the opinion of different users and political camps (the four aforementioned labels) toward `OddEven` experiment. To do so, we use sentiment analysis as a mean to quantify the opinion. We are mainly interested in measuring whether people and groups expressed positive, negative, or neutral opinions. We use a method introduced by Thelwall et al. called "Sentistrength" to quantify the sentiment of individual tweets [19]. This method is reported to be effective and has been specifically designed to deal with short-text shared on social media platforms. We also use LabMT to assess the sentiment trend of different political groups [11]. LabMT is known to perform better and more accurately for large pieces of text, which is the case when we concatenate all tweets posted by the members of a given political camp. For both cases, we compute sentiments over time (on daily basis) and for different topics related to `OddEven` experiment, namely: air quality, traffic congestion, and public transportation. It is important to recall that as per the official notification of `OddEven` [4], the objective was to curb air pollution and no mentions were made to improving traffic congestion nor to the impact on public transportation. However, because of the very nature of the experiment, we thought that it would be interesting to see what people thought about those two related topics.

5 RESULTS AND DISCUSSION

We report in this section the main findings of our analysis. We first present how good one can infer the political leaning of users using different types of data from Twitter and different methods. We then analyze opinion and sentiment trends observed in different configurations of time, geographical location and topics.

5.1 Inferring Political Leaning

The first task was to infer the political leaning of users on Twitter. By mining biographies – a short text used by Twitter users to describe themselves and their interest on Twitter – we identify users who publicly expressed their political affiliation and we use them for training. Among the set of 64K users that we have, we searched for all those who mentioned AAP, BJP, or any other term related to these two political parties (e.g., names of prominent personalities) in the biography field of their Twitter accounts. Next, we manually read the found biographies and correctly label them as belonging to one of the classes of interest. This step was important to discard users who may mention political camps related terms but do not endorse them. This is for instance the case of a user who would express that he dislikes a given political personality. Thus, we obtained 3,300 Twitter accounts, 944 are labeled as AAP supporters (AAP is ruling the state of Delhi) and 2,381 labeled as BJP supporters (BJP is ruling India.)

Examples of positive and negative mentions of political parties in biographies are given below.

E.g., 1: *"I support Narendra Modi and BJP fan of akshay kumar tweets related to Indian politics only and international affairs"* **@ProudHDL**

E.g., 2: *"Die-hard AAP supporter. Hoping for a corruption free India"* **@AAPkSaath**

E.g., 3: *"Corporate lawyer, hates AAP."* **@Abhisheksaket**

E.g., 4: *"Bad AAP is hundred miles ahead of good BJP. Still."* **@CanfuseBird**

Users who authored the first and second biographies have clearly expressed their strong endorsement of BJP and AAP parties respectively. The author of the third biography expressed a strong negative opinion about AAP. Without manual checking, we would have labeled this user as being an AAP supporter. The fourth example is very interesting in that the user mentions the two political parties AAP and BJP. Reading the tweet allowed us to correctly detect the AAP leaning of the user, hence to correctly label her.

Next, we built a multi-class Support Vector Machine (SVM) classifier to classify users into four different political camps: AAP supporters, BJP supporters, bi-political, apolitical. Given the known difficulty of inferring the political leaning of users[8], we tested the classifier with different feature combinations: (1) Hashtags (2) Friendship network (3) Mention network (4) Hashtags & Friends. (5) Hashtags & Mentions. (6) Friends & Mentions. For every set, we consider top 10% shared features (example: top 10% shared Hashtags) used by all users.

Table 2 summarizes the obtained results for every classifier. Clearly, the Friends features-set outperforms all other combinations in terms of F1 score. Yet, the eye scanning of the results revealed they are not as good as one would expect. Thus, inspired by the predictive power of the friendship network (recall that friends are people that a user follows on Twitter) we used another intuitive approach to determine the political affiliation of users (DirectFriendship). We first identified political leaders from both parties: BJP and AAP. Next, we use a simple heuristic to label users into one of the four political camps we created. Users who only follow the BJP leaders on Twitter are labeled as BJP supporters and users who only follow AAP leaders are labeled as AAP supporters. Similarly, users who follow leaders from both parties are labeled as Bi-political whereas those who do not follow any of the leaders are labeled as Apolitical. The last row in Table 2 shows that the intuitive and straightforward method outperforms all SVN based classifiers.

Table 2: Performance of the multi-class SVM classifier in predicting the political camp of users using different features

Features	# Features	Accuracy	Precision	Recall	F1
Hashtags (H)	1181	0.685	0.722	0.617	0.665
Friends (F)	2455	0.716	0.735	0.685	0.709*
Mentions (M)	2307	0.700	0.728	0.649	0.686
H & F	3636	0.718	0.744	0.671	0.705
H & M	3488	0.716	0.746	0.658	0.699
F & M	4762	0.735	0.761	0.662	0.708
Dir. Fri.	-	0.951	0.966	0.973	0.959

5.2 Political Bias vs. Personal Experience in Shaping Human Perception

At this point, and based on our ground reality analysis, we can say the `OddEven` experiment missed its objective in reducing air pollution, but the road traffic congestion which was not the main target of the experiment did improve. One of the co-authors did visit Delhi during the experience and has confirmed to us this observation. In what follow, we give some examples of tweets that corroborate our ground findings:

E.g., 1: *"So basically, #OddEven rule didn't fix pollution but cleared Delhi's traffic jams. Not a complete failure then, huh?"* **@SudhishKamath**

E.g., 2: *"Don't know abt pollution, but the #DelhiOddEven formula is definitely solve traffic problem and going to save millions in form of fuel"* **@vikas_ch**

E.g., 3: *"It is so ODD that EVEN on a Monday morning the traffic is so smooth in Delhi. #DelhiOddEven"* **@am46an**

The question now is to know what supporters of different camps said about the experiment in general, and about air pollution and traffic congestion in particular. Recall that `OddEven` was subject to political polarization as AAP who implemented the experiment claimed its usefulness whereas BJP has put it in doubt.

We started by associating every tweet authored by a user to a political camp to which she belongs. For every camp, we aggregate the sentiment of its members per time intervals of one day. We use LabMT for this task. Figure 6 illustrates different camps sentiment over time. Sentiment scores ranges in [1,9] interval with 1 being the less positive value and 9 the most positive one. The visual inspection reveals a clearly that AAP supporters are more positive (enthusiastic) about OddEven compared to their BJP counterparts. The Pearson correlation between the sentiment time series if AAP and BJP supporters is equal to 0.1465.

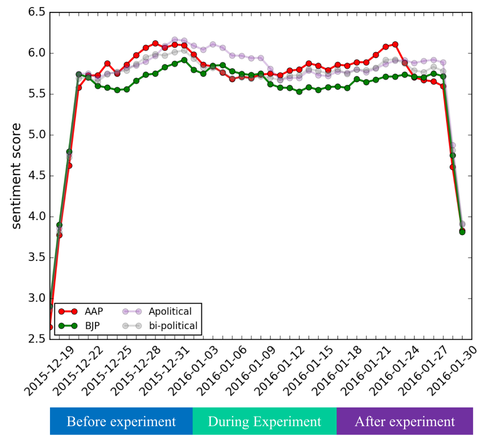

Figure 6: Overall sentiment over time of the four different political camps. AAP supporters are significantly more positive than BJP supporters.

However, when we limited the analysis to only users living in Delhi to remove noise from people expressing opinions without having a personal experience of OddEven, we found the the differences in opinion were less significant as shown in Figure 7. Thus, we recomputed the Pearson correlation score between the sentiment time series of the two camps, by considering only members living in Delhi, and found that it jumped to 0.2587. This means that the global trends of opinion for BJP where driven by the mass of users who did not experience OddEven and yet decided to align with the positions of their political party.

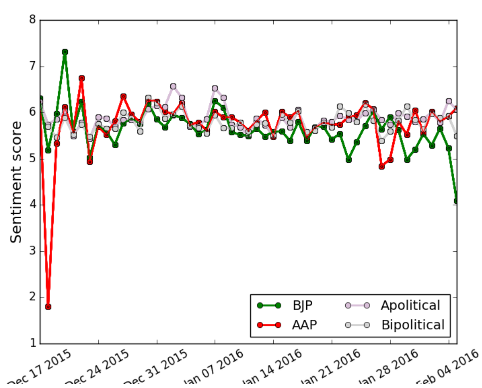

Figure 7: Sentiment score on tweets of tweets about *OddEven* authored by users living in Delhi

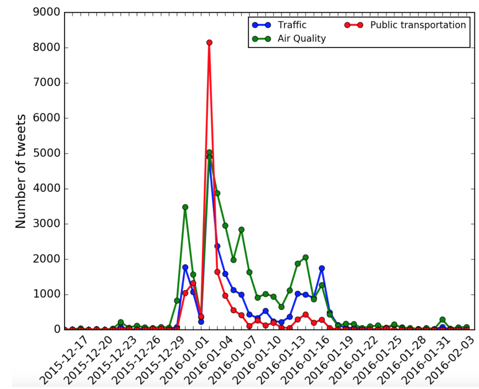

Figure 8: Distribution of tweets about Air Quality, Public Transportation, and Traffic Congestion over time

Table 3: Number of positive/negative tweets posted by each camp over time. Most of the tweets lay in the apolitical and bi-political camps.

Camp/Time	Anticipation	Experience	Recollection
AAP	$103^{+}/144^{-}$	$3470^{+}/2319^{-}$	$1256^{+}/722^{-}$
BJP	$74^{+}/120^{-}$	$1746^{+}/1617^{-}$	$374^{+}/504^{-}$
Apolitical	$321^{+}/506^{-}$	$14490^{+}/8117^{-}$	$3327^{+}/2274^{-}$
Bi-political	$2137^{+}/2641^{-}$	$62692^{+}/50900^{-}$	$22482^{+}/14706^{-}$

To enable a fine grained analysis, we used SentiStrength [8] tool to label individual tweets as positive, negative, or neutral. Thus, we could aggregate sentiment at the level of individual users and have it tracked over time. Table 3 shows the distribution of the number of positive and negative tweets by camp and time. We refer to these tweets as opinionated tweets (in contrast to neutral tweets.) We can see that number of opinionated tweets during the experiment (experience phase) is high in both camps varying between 3000 and 5000 tweets, but this burst faded out after this period. Moreover, we can see that the overall volume of opinionated tweets lay inside bi-political and apolitical camps.

Figure 8 illustrates the distribution over time of tweets volume corresponding to different topics. We use manually curated keyword dictionaries related to different topics in order to classify tweets into: air pollution, traffic congestion, and public transportation. Note that one tweet can belong to different topics if its content match keywords from different lists. Interestingly, we found that all topics received most of their contributions at the beginning of the experiment. For instance, one of the most noticeable burst is on the first three days of OddEven that were off days (concatenation of a long weekend and beginning of year's holidays.) Another interesting observation is that air quality was the main discussed topic in the anticipation phase, followed by congestion and public transportation. This is mainly due to the fact that the main reason for implementing OddEven was to reduce air pollution.

Next, we will share our findings regarding the three topics separately. For each topic, we report the volume of opinionated users as

[8] http://sentistrength.wlv.ac.uk/

well as the negativity and positivity in each camp in order to capture the evolution of users engagement in the six weeks of the study. In addition, we introduce the location dimension to have a closer inspection on the opinion of users who had personal experience of OddEven.

5.2.1 Air Quality. We start our topic-centric analysis by studying tweets about Air Quality in the context of *OddEven* experiment. Notice that we interchangeably use Air Quality and Air Pollution to refer to the same topic. Figure 9(a) illustrates the number of opinionated users in the three time periods. A user is considered as opinionated if she has more opinionated tweets than neutral tweets. We see that people started talking about the experiment before it took place as the expectations were very high (anticipation period). Needless to say, the media has focused on the pollution aspect as Delhi is one of the most polluted cities in the world [2]. Figure 9(b) reports the percentage of positive users over different periods of time. For people with political leaning, the percentage of positivity in general has increased during the two weeks of the experiment. More specifically, the expectations of AAP supporters were high (they started with 37% of positive tweets), but this has somewhat decreased to 15% during the first week of the recollection period. BJP supporters on the other side remained skeptical throughout the experiment. Indeed, we see that during all the periods, positive tweets varied between 12% and 18% only. Generally speaking, people with no political drive have had a negative opinion about Air Quality. For instance, during the experiment, the percentage of positive tweets was as low as 12%. Despite the huge difference in the number of users in bi-political and apolitical groups, we found that they share similar views, which are well aligned with the ground truth.

Next, we introduced the location dimension to capture the effect of personal experience of reality. Location of users is extracted from the "location" attribute of their Twitter profiles. We distinguish three different locations: Inside Delhi, Inside India (but not in Delhi), and Outside India. In Figure 10(a) that illustrates the number of users who are discussing Air Quality in Delhi over time period together with their sentiment, we see that AAP and BJP supporters are equally negative about the topic. However, when we looked at people who live in India but outside Delhi (Figure 10(b)), we found the number of BJP supporters who discussed air quality to be more than the number of AAP supporters. This is related to the fact that BJP is a national and old party, while AAP is a new party promising to bring change to the traditional political system. The same pattern is outlined in Figure 10(c) for people living outside India.

5.2.2 Traffic Congestion. After Air Quality, we shed some light on the traffic congestion topic in the context of OddEven experiment. Figure 11 (a) illustrates the number of opinionated users at different phases of the experiment. The figure shows that bi-political group is over taking other groups in terms of volume of positive tweets. Having the distribution of tweets is interesting in this case to highlight the fact that the topic was not a main focus during the "anticipation" period (with a maximum of one hundred unique engaged users in all camps). However, congestion has popped up during the experiment where the number of users varied between 550 and 2000 users in different camps. Figure 11(b) reports the percentage of opinionated users over time periods. As the number of tweets was very low before the experiment, it is difficult to generalize any observed pattern, even though one can see that most of the tweets were positive. The percentage of positive users varied between 50% and 60% in AAP camp, more than any other camp. BJP supporters were skeptical, only 40% of users in this camp were positive about the improvement in traffic congestion. Another observation that can be made is that traffic congestion is a very localized problem that varies from a neighborhood to another. This is different from air quality where people in the same city breath "almost" the same air. Thus, opinion on traffic can vary from neighborhood to another. As we do not have enough geo-coded tweets, we could not deepen our analysis to provide high-resolution spatial analysis.

Similarly to the previous analysis, we introduce the location dimension in our analysis to see how people who have witnessed the experiment reacted compared to the outsiders. Figure 12 presents the number of users who engaged with traffic topic in Delhi. We see that bi-political camp was the most engaged among other camps. In terms of sentiment, we see that AAP supporters were more positive in Delhi. The figure also shows that BJP supporters in India engaged in the discourse about traffic more than those in Delhi, due to the fact that BJP is a big national party. BJP engagement was negative. Surprisingly, we found that the number of BJP supporters living outside India who engaged in the discussion was higher than those living in India which reveals the international echo of OddEven.

5.2.3 Public Transportation. Now, we present results related to Public Transportation in the context of OddEven experiment. Figure 13(a) shows the number of positive users. We observe that this topic did not generate lots of discussions on Twitter, except during the two weeks of the experiment (experience period). This could be due to the fact that public transportation was directly linked to the scope experiment. This is in contrast for instance with the way Paris implemented its 2 days of OddEven in which authorities have made all public transportation free[3]. However, digging a little bit, we could see some tweets referring to newspapers mentioning that public transportation did handle the huge surge in ridership demand [9]. Figure 13(b) reports the percentage of positive users over time in different camps. The percentage of positivity is varying from period to another, but we observe that most of the groups are torn between support and opposition. During the experiment, the fraction of positive users in most of the groups varied between 48% and 60%. That is to say that public transportation was the least polarized topic among others, probably because it was not part of the political discourse that developed around OddEven.

6 CONCLUSION

We present in this paper our finding about the role of political affiliation on human perception. Our case study was OddEven– a live real-world and large-scale experiment run in Delhi that had direct implications on how people move in their city. To conduct the study, we combined data from different sources: Twitter to capture the public discourse, CPCB Program (ministry of environment) to measure the effectiveness of the experiment in reducing air pollution, and Google Traffic API to estimate the impact on traffic congestion. We used state of the art machine learning techniques to infer political leaning and sentiment of users toward.

[9] http://goo.gl/sPCtoU, http://goo.gl/U1cnPR

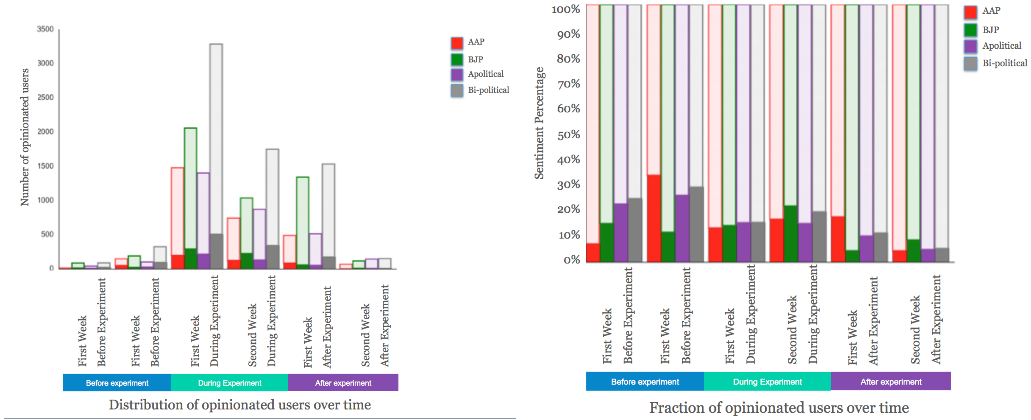

Figure 9: Distribution of opinionated users + Normalized distribution of users discussing Air Quality topic over time

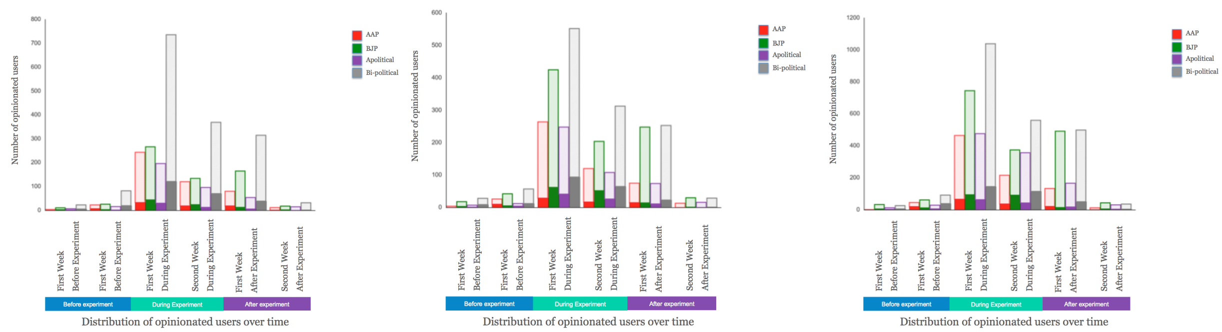

Figure 10: Fraction of opinionated users in Delhi, India, and outside India discussing Air Quality topic over time

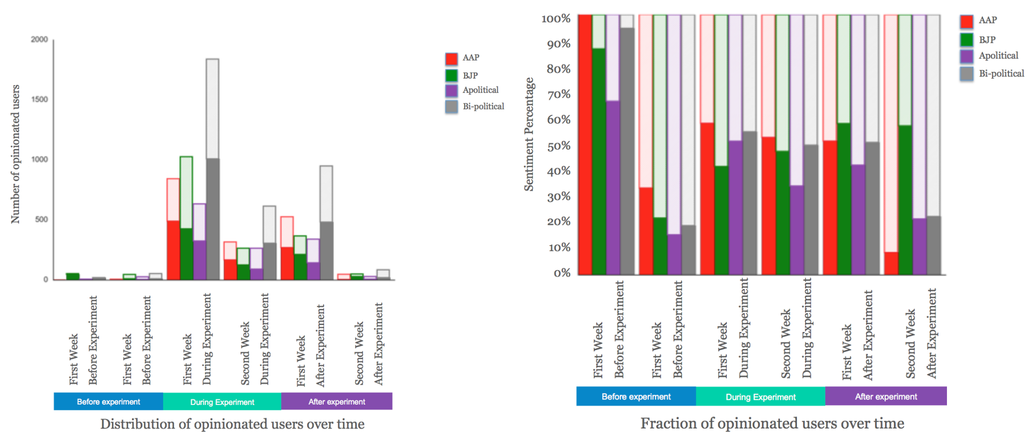

Figure 11: Temporal distribution of opinionated users + Normalized distribution of users discussing traffic congestion

Our findings reveal a strong alignment between people perceptions and positions of the political parties to which they belong. This is particularly amplified in cases where people are not exposed to the realities on the ground. Luckily, we found that personal experience does help people formulate objective opinion and overcome political biases. For instance, BJP supporters living in Delhi tended to be less skeptical about `OddEven` when compared to their fellows in BJP who live outside Delhi. This analysis shows that combining social networks data together with physical sensing spaces provides a fertile ground to study large-scale urban experiments. For the

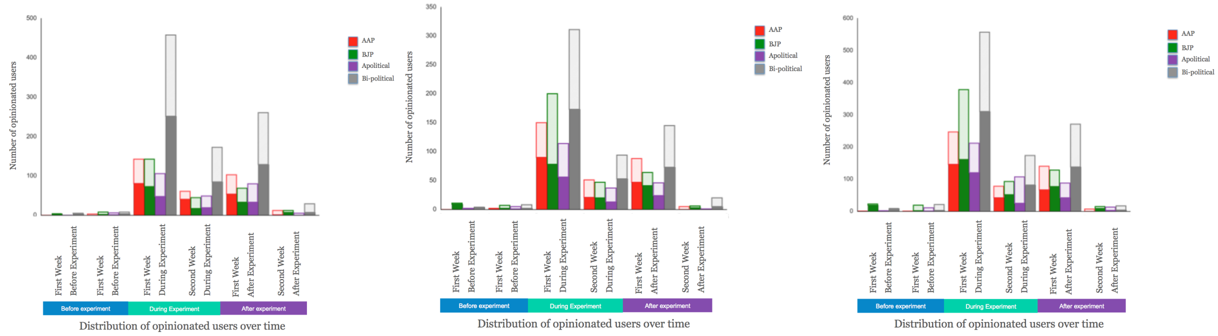

Figure 12: Fraction of opinionated users in Delhi, India and outside India discussing Traffic topic over time

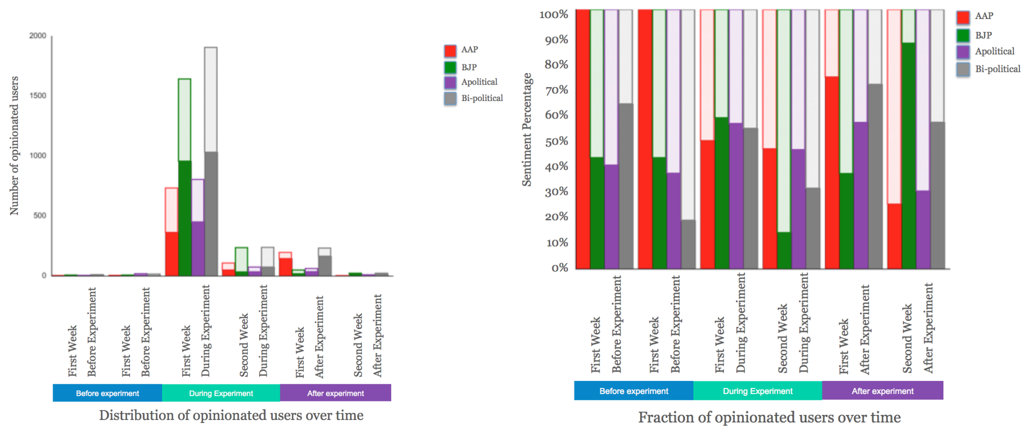

Figure 13: Distribution of opinionated users + Normalized distribution of users discussing Public Transportation topic over time

future, we aspire to go beyond studying `OddEven` experiment the role world-views in shaping human perception and objectivity in other settings.

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